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Original Article

Immune Based Optimal Multicast Routings in Vehicular Ad hoc Network

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Abstract *- In this paper multicast routing plan has been solved using the Artificial Immune System (AIS) algorithm. VANET faces various issues due to their highly dynamic topology, including frequent movement and rapid changes, which can result in delays and data packet loss. Due to its highly dynamic and complex networks, it requires efficient multicast routing for Intelligent Traffic System (ITS) applications such as traffic control, collision avoidance, and emergency services. The proposed approach utilizes the clonal selection method for optimising the route selection process to ensure reliable and efficient data delivery along the shortest path. To tackle these issues, the current study deals with location-based routing protocols over other VANET routing protocols. These protocols utilise the geographical location information of vehicles to make routing decisions instead of pre-defined route entries.*

Keywords *- VANET, Multicast routing, Artificial immune system, Clonal selection, Greedy forwarding, Packet delivery rate.*

1. Introduction

VANET has turned out to be a promising method to enable and support intelligent transportation systems and improve road safety, traffic efficiency, and driver experience. VANETs consist of vehicles equipped with communication devices that can share data with roadside infrastructure. Effective routing in VANETs is critical to enable efficient and reliable communication among vehicles and infrastructure components. VANET-enabled vehicles could receive information about the optimal route based on current traffic conditions, helping to avoid congestion and reduce travel time [1,2]. To overcome the limitations of traditional routing protocols, researchers have explored the use of nature-inspired optimisation algorithms for VANET routing. These algorithms, inspired by natural phenomena and behaviours, aim to find efficient and adaptive routes in dynamic environments [3].

The firefly algorithm is a nature-inspired optimisation algorithm that imitates the flashing behaviour of fireflies. The algorithm works by simulating the flashing behaviour of fireflies, where each firefly is attracted to others based on its brightness, and the brightness of a firefly is determined by its fitness value [4]. The firefly algorithm has been used to solve various optimisation problems, including clustering, scheduling, and routing. The firefly algorithm has been used to solve the multicast routing problem in VANETs due to its ability to handle dynamic network topologies and its fast convergence rate [5]. The results showed that the firefly algorithm outperformed the other algorithms in terms of delay and throughput. The firefly algorithm was also able to handle dynamic network topologies but it requires a large number of iterations and a high computational cost [6].

Genetic algorithm has been used to solve the multicast routing problem in VANETs due to its ability to handle dynamic network topologies and ability to find global optima. Even though the genetic algorithm was able to handle dynamic network topologies and find global optima, it may suffer from premature convergence and a high computational cost [7]. Particle swarm optimization for multicast routing in VANETs works by using a population of particles to explore the search space and find the optimal multicast routing solution. The particles adjust their positions based on their own experience and the experience of their neighbours, and the algorithm updates their position and velocity until it converges on the optimal solution [8,9]. In the context of multicast routing in VANETs, the bee colony algorithm represents the potential multicast routes. Each employed bee is associated with a position in the search space, which represents a possible multicast routing solution. The algorithm uses these bees to explore the search space and find the optimal multicast routing solution [10]. The employed bees explore the search space, the onlooker bees select the best solutions to follow, and the scout bees generate new solutions to explore new areas of the search space [11]. Typical drawbacks of this algorithm are the potential for lack of adaptiveness, premature convergence, slow convergence, and sensitivity to parameters.Ant colony optimization for multicast routing in VANETs works by using a population of artificial ants to explore the search space and find the optimal multicast routing path. The ants build solutions by sequentially visiting nodes based on the pheromone trail that they detect. The algorithm updates the pheromone trail based on the quality of the solutions found by the ants until it converges on the optimal solution [12,13].

Neural networks for multicast routing in VANETs work by learning the relationship between input features and the optimal multicast routing path during training. The network adjusts its weights to minimize the difference between its predicted output and the actual output [14]. Once trained, the network can be used to predict the optimal multicast routing path for new input features based on the learned patterns and relationships.For the first time, the current study deals with the implementation of artificial immune systems for solving multicast routing in VANET.

This paper particularly concentrates on the clonal selection method for solving the multicast routings in terms of distance between the vehicles available in the dynamic mobility environment.

2. VANET Structure

Vehicular Ad-hoc Networks (VANETs) have gained significant attention in recent years due to their potential to revolutionize transportation systems and enhance road safety, traffic efficiency, and driver experience.VANETs consist of vehicles equipped with wireless communication capabilities, allowing them to exchange information with each other and with roadside infrastructure, as shown in Figure 1.

The architecture of VANETs can be categorized into three main components: On-board Units (OBUs), Road Side Units (RSUs), and the communication infrastructure. OBUs are the communication devices installed in vehicles, responsible for collecting and disseminating information. They enable Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, allowing vehicles to exchange data with nearby vehicles and RSUs

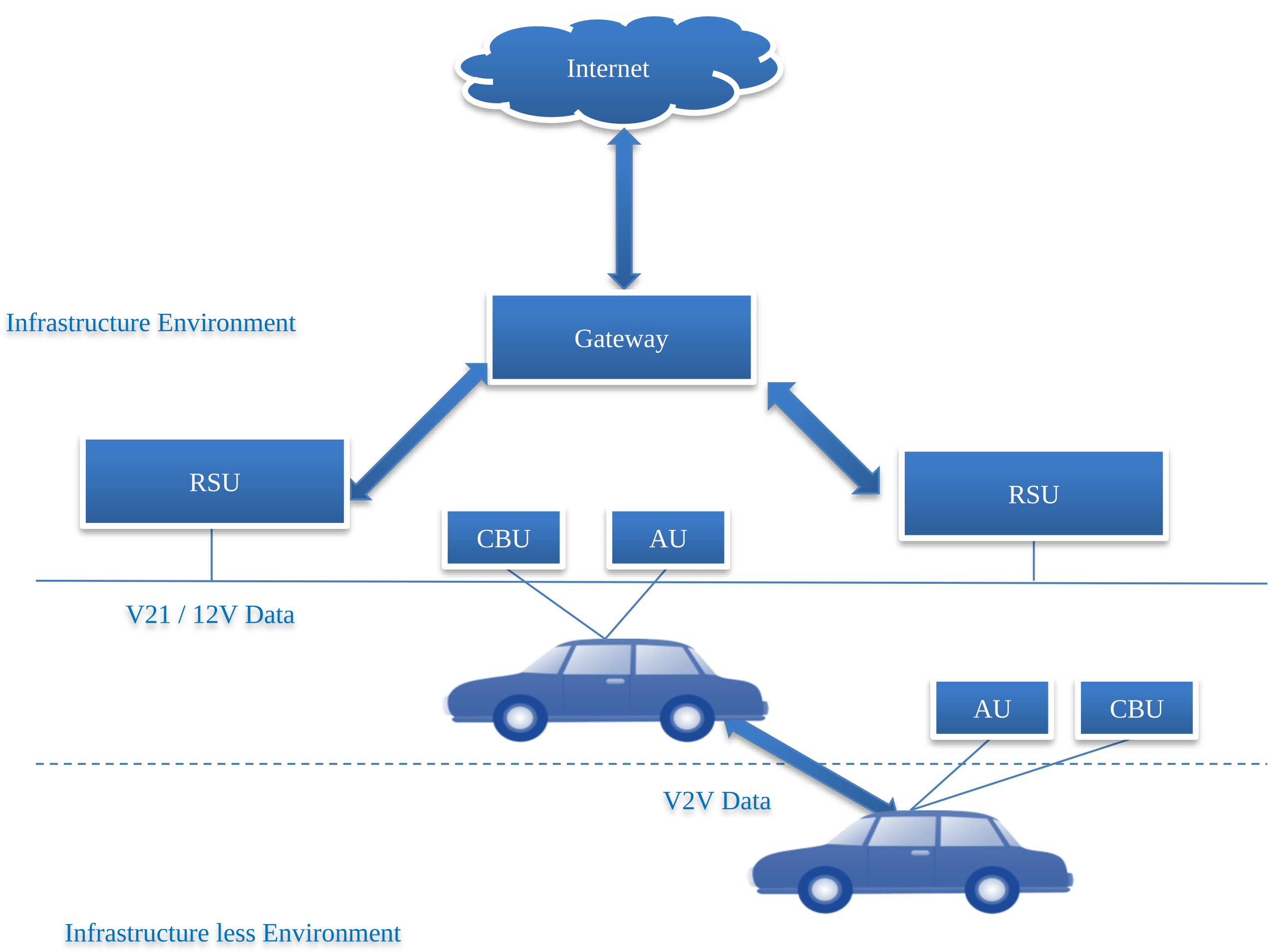

Fig. 1 Typical VANET architecture

Routing in VANETs faces unique challenges due to the moving topology of vehicles. Vehicles constantly move, change their positions, and create dynamic network topologies. Moreover, VANETs are characterised by high node mobility, intermittent connectivity, and varying channel conditions. These factors pose significant challenges for designing efficient and reliable routing protocols in VANETs.

The objective of an efficient VANET focuses on evaluating the performance of the multicast routing algorithm using appropriate metrics. Transmission pickup proportion, entire latency, networking overhead, scalability, energy usage, and QoS parameters are a few examples of possible metrics.

Extensive simulations under various VANET scenarios, taking into account varying vehicle concentrations, traffic patterns, and network conditions, are taken into consideration in the current study.

3. Mathematical Modeling

To assess the performance of VANET routing protocols, several evaluation metrics are commonly used. These metrics help in comparing and analyzing the protocols based on their efficiency, effectiveness, and suitability for different VANET scenarios. Some of the key evaluation metrics include:

- Packet Delivery Ratio (PDR): It measures the ratio of successfully delivered packets to the total number of transmitted packets, indicating the protocol's reliability in message delivery.
- End-to-End Delay: It quantifies the time taken for a packet to travel from the source to the destination, reflecting the protocol's efficiency in message propagation.
- Network Overhead: It represents the amount of additional control and signaling traffic generated by the routing protocol, affecting the network's bandwidth utilization and efficiency.
- Scalability: It measures the protocol's ability to handle an increasing number of vehicles and adapt to changes in network size without significant performance degradation.
- Energy Efficiency: It evaluates the energy consumption of the routing protocol, which is crucial in VANETs where vehicles have limited power resources.

3.1. Fitness Formation

The above-discussed evaluation metrics can be optimized by selecting the nearest node to the source node.
Therefore, the fitness function

$$\lambda_{i,j} = [D_{Euclidean}]_{i,j} \tag{1}$$

Where, $\lambda_{i,j}$ represents the fitness value while connecting i^{th} and j^{th} nodes in the VANET $[D_{Euclidean}]_{i,j}$ denotes the Euclidian distance between the i^{th} and j^{th} connected nodes.

$$[D_{Euclidean}]_{i,j} = \sqrt{(i_x - j_x)^2 + \left(i_y - j_y\right)^2} \tag{2}$$

$\left(i_x, i_y\right)$= Position representation of i^{th} node in the network
$\left(j_x, j_y\right)$= Position representation of j^{th} node in the network

The current methodology provides a systematic approach for achieving optimal and shortest paths in a network, considering varying densities, communication ranges, and dynamic conditions.

4. Artificial Immune System

The Artificial Immune System (AIS) is a biologically inspired evolutionary algorithm to solve a wide range of engineering problems. AIS mimics the structure of the immune system and how the immune system responds when antigens are attacking it[15].

There are three types of immune algorithms in practice to solve optimization problems:

1. Clonal selection
2. Negative selection
3. Immune network theory

4.1. Clonal Selection System

This algorithm is used for finding suitable antibodies when antigens or invaders attack the immune system. The selection is done according to the affinity strength of antigen-antibody interactions[16]. The flow process of a typical selection theory is represented in Figure 2.

4.2. Negative Selection Algorithm

This algorithm deals with the recognition of self-reacting antibodies and deleting the same when antigens attack the immune system. This algorithm improves the efficiency of the immune system. The flow process of a typical negative selection theory is represented in Figure 3.

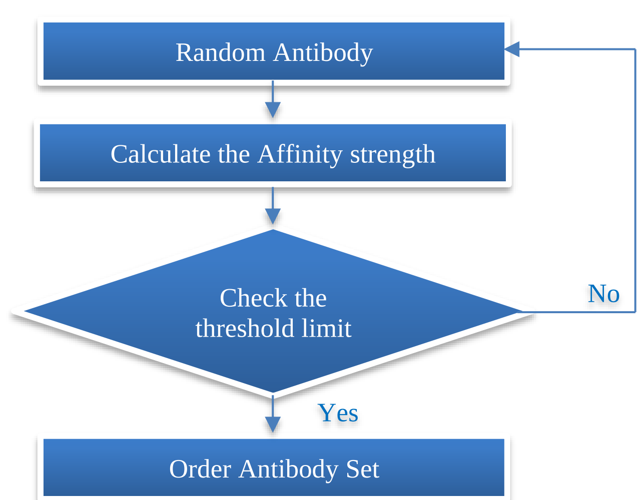

Fig. 2 Flow diagram of the clonal selection algorithm

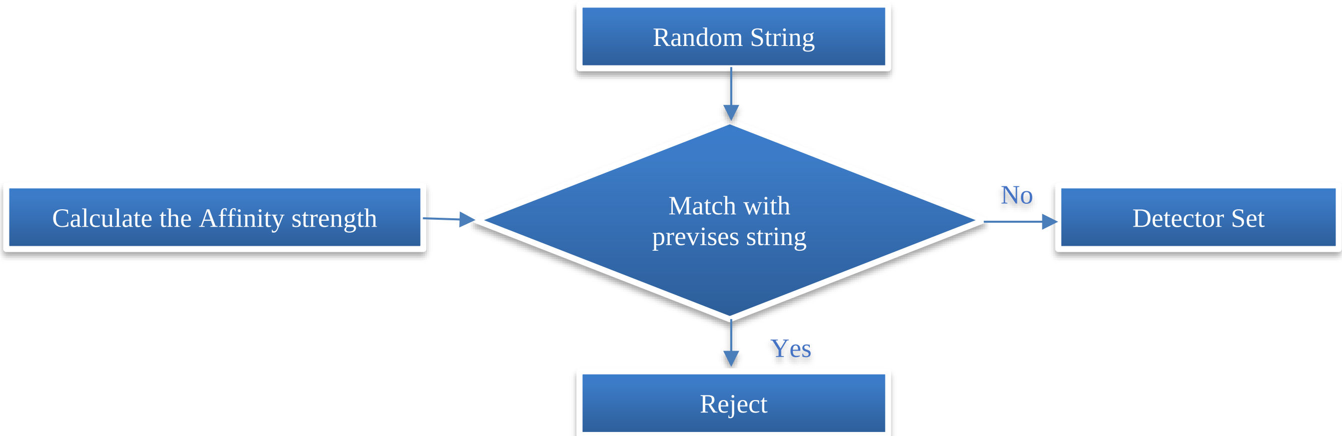

Fig. 3 Flow diagram of the negative selection algorithm

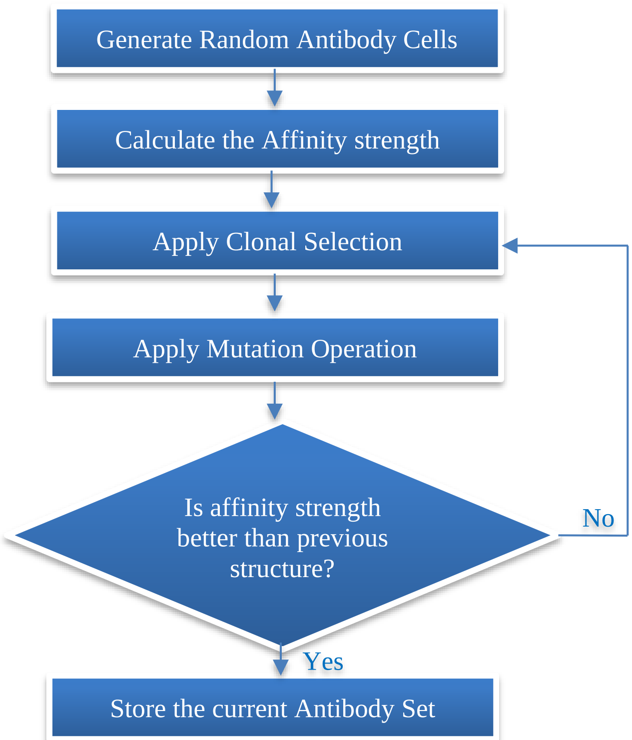

Fig. 4 Flow diagram of immune network algorithm

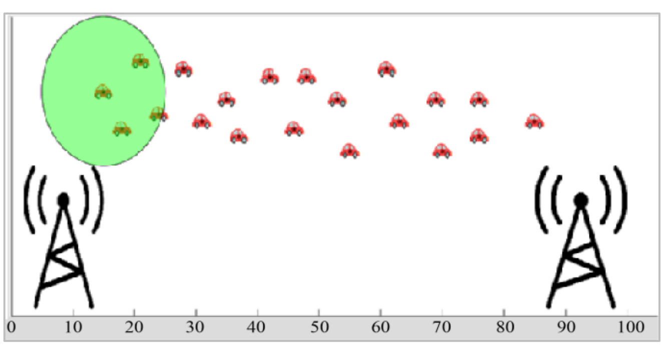

Fig. 5 Representation number of vehicles, first vehicle OBU range and RSU range

4.3. Immune Network Algorithm

This algorithm forms a network structure with a group of antibodies to increase the affinity strength for neutralizing the invaders when the immune system is attacked. The flow process of a typical immune network theory is represented in Figure 4.

5. AIS Implementation

The current study deals with the implementation of two AIS algorithms named clonal selection and negative selection to solve multicasting in VANET.

5.1. Implementation of Clonal Selection Algorithm

Initially Clonal Selection Algorithm (CSA) is implemented to find the suitable node for beacon transmission, multicasting in VANET as follows:

It is taken into consideration that RSU is installed at the roadside, which has a range capacity of 100m and an OBUE range as 10m.as shown in Figure 5. At a specified time vehicle network will be formed and is considered as dynamic at each instant of time.

Table 1 represents the similarities of CSA with VANET structure multicast for the implementation in order to choose the node positions for transmitting the beacons as per the user need. Similar to the immune structure property, the antibody (vehicle node) will be selected according to the affinity strength (distance between the antibody and antigen nodes) when reacting with the antigens, as represented in Figure 6.

Table 1. Similarities of CSA with VANET multicast structure

S.no.	Clonal Selection Parameter	VANET structure Parameter
1	Antibody	Node / Vehicle in the network
2	Antigen	Other nodes except the antibody node
3	Affinity strength	Distance between the antibody and antigen nodes

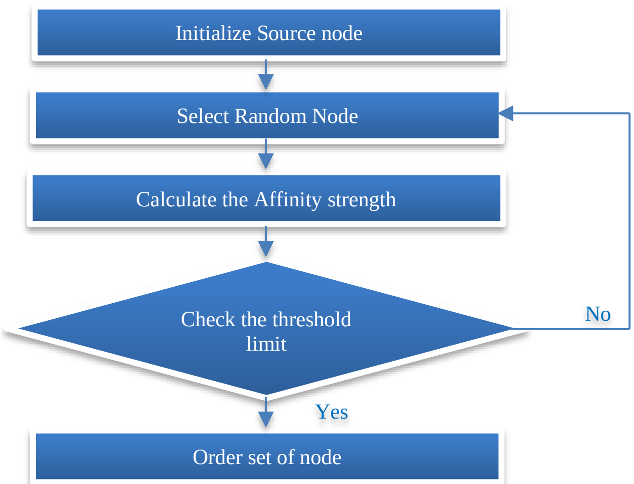

Fig. 6 Implementation of the clonal selection algorithm

5.2. Implementation of the Negative Selection Algorithm

Once the clonal selection is implemented, the nodes will be selected that are satisfied the affinity value. However, there is a possibility of reconsideration of nodes as at each cycle, the random node is considered at the clonal selection stage. In order to avoid such ambiguity, a Negative Selection Algorithm (NSA) is implemented. The flow process of NSA for multicast routing in VANET is illustrated in Figure 7.

6. Results and Discussion

The proposed methodology is implemented for the scenario, which has the following parameter settings, as illustrated in Table 2.

The environment is considered in the MATLAB 2014 version to validate the proposed methodology. At a specific instant, it is assumed that RSU identifies 20 number of vehicles (N). Since each vehicle has its OBU range of 10m. it generates 39 number of edges (E), as represented in Figure 8.

Table 2. VANET parameter consideration

S.No.	Description	Value
1	Number of vehicles	20
2	RSU Antenna range	100 m
3	OBU Range	10 m
4	Packet size	64 bytes
5	Mobility Model	Random waypoint
6	Traffic model	Constant bit rate
7	Propagation model	Two-way Ground
8	MAC protocol	IEEE 802.11

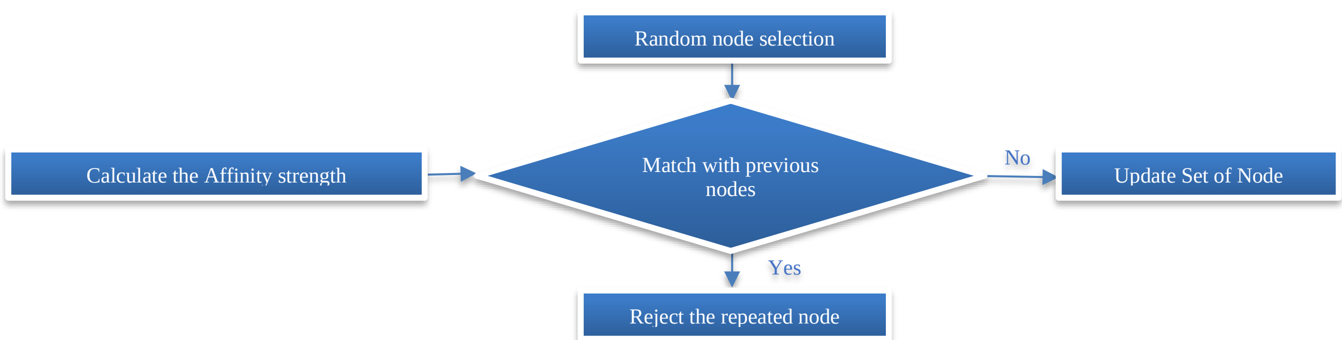

Fig. 7 Implementation of the negative selection algorithm

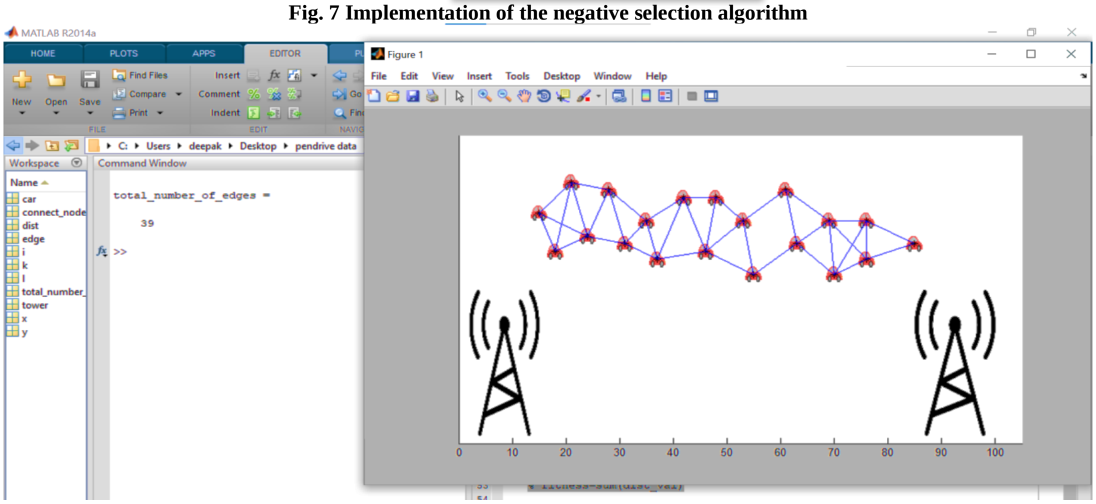

Fig. 8 Network formation in a simulated environment

Table 3. Results during the first run

S.No.	Parameter Description	Value
1	Nodes Sequence	1-4-6-7-9-10-12-14-16-19-20
2	Number of hops	11
3	Affinity Strength between hops	9.48; 7.071; 5;7.61; 8.06; 8.06; 8.94; 8.94; 8.60; 9.21
4	Affinity strength of solution	81.006

Once the network is formed and source and destination nodes are identified, a message transmission tree should be generated. In this study we consider the optimal criteria regards to the minimum possible distance to transfer the beacons to the source vehicle from the destination vehicle.

After executing the methodology in the simulation environment (Figure 9), the results, as tabulated in Table 3, are obtained for the first run.

The solution towards the multicast routing obtained for the current situation of vehicles as '1-4-6-7-9-10-12-14-16-19-20' in the scenario of the source node as '1' and the destination node as '20'.

Since each run comprises with random selection of antibodies, there is a chance of a stochastic nature in the proposed methodology.

Therefore, the program is run 10 times to avoid such limitations and obtain optimal solutions. The results for the iterations are represented in Table 4, and the figures for each iteration are illustrated in Appendix I.

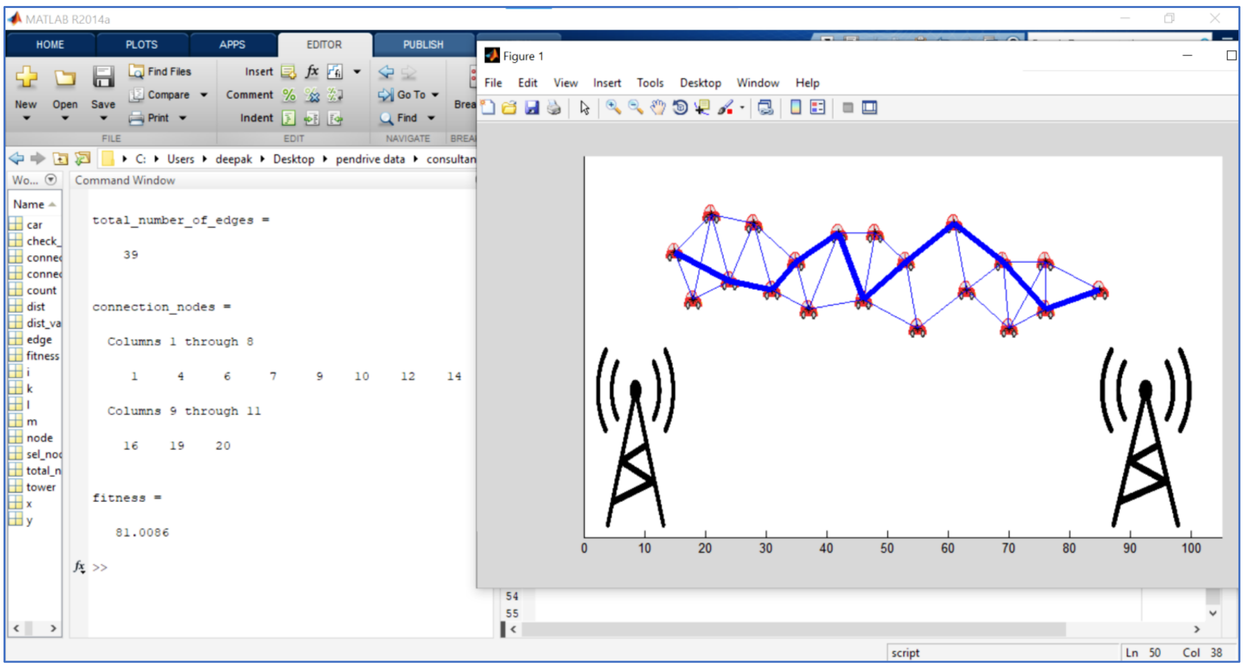

Fig. 9 Simulation results for the first run of AIS algorithms

Table 4. Simulation results for program execution in the same environment

Run Number	Nodes Sequence	Number of hops	Affinity strength of solution
1st	1 4 6 7 9 10 12 14 16 19 20	11	81.006
2nd	1 3 5 6 7 9 10 12 13 15 16 18 19 20	14	94.7904
3rd	1 4 6 8 9 11 12 14 15 17 19 20	12	83.9781
4th	1 2 3 5 7 9 10 13 15 17 19 20	12	88.1666
5th	1 2 4 6 7 8 9 10 11 12 14 15 16 17 19 20	16	105.7668
6th	1 3 4 6 7 9 11 12 14 15 17 18 19 20	14	94.0704
7th	1 4 6 7 9 11 12 14 15 17 19 20	12	80.8354
8th	1 4 6 8 10 12 14 15 16 19 20	11	80.7546
9th	1 3 4 6 7 8 10 13 15 16 17 19 20	13	89.093
10th	1 2 3 5 6 8 10 13 15 16 18 19 20	13	91.7434

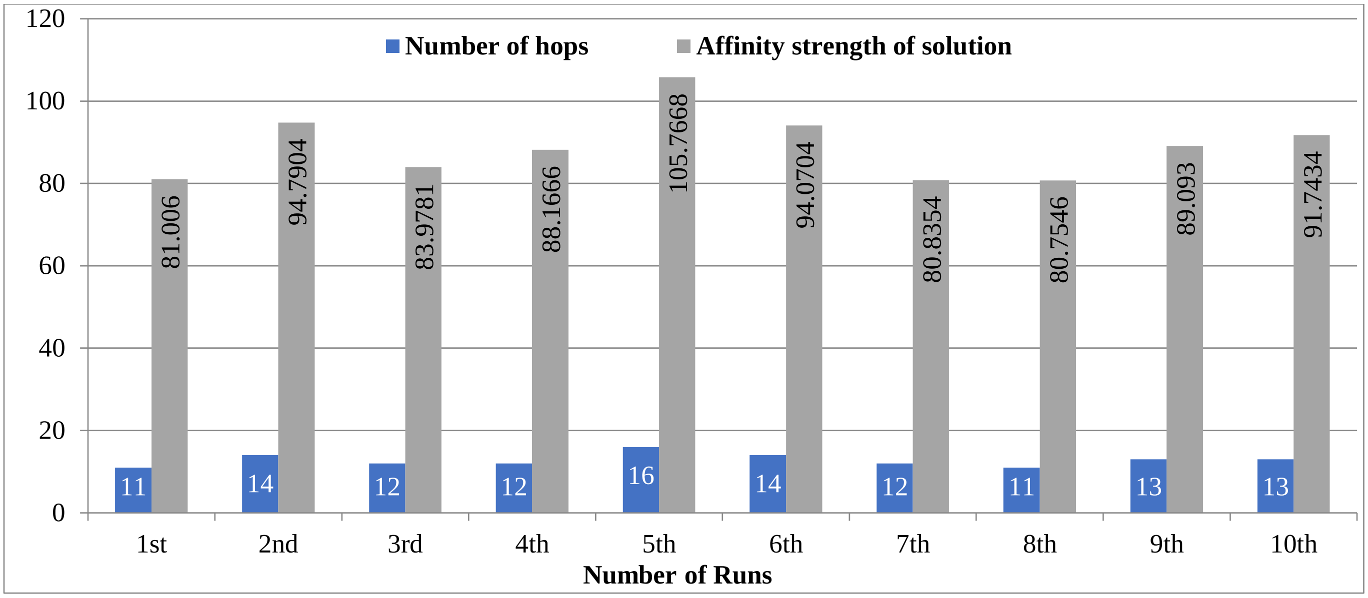

Fig. 10 Simulation results for 10 runs

From the generated results, it is noticed that two runs viz. 1st run and 8th run with a minimum number of hops, i.e. 11 hops. However, the optimal fitness value was found in the 8th run with a total affinity value of 80.7546. A clear graphical representation of the results is shown in Figure 10.

7. Conclusion

In this research work, intelligent multicast routing has been implemented in vehicular communications using artificial immune systems. Multicast routing is performed based on objective criteria of minimum affinity. The method initially starts with a clonal selection algorithm for identifying suitable nodes. Later, a negative selection method is implemented to eliminate duplicate nodes in the network. Finally, case studies were presented in order to validate the performance of the proposed methodology. Results showed that the proposed method exhibits its various advantages such as energy efficiency, Minimum Delay and fast transmission of packets etc.

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Appendix

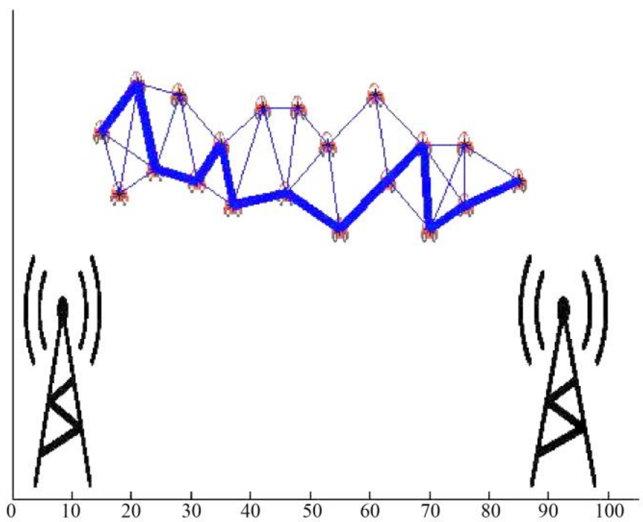

Fig. A1 Simulation results of 2nd run

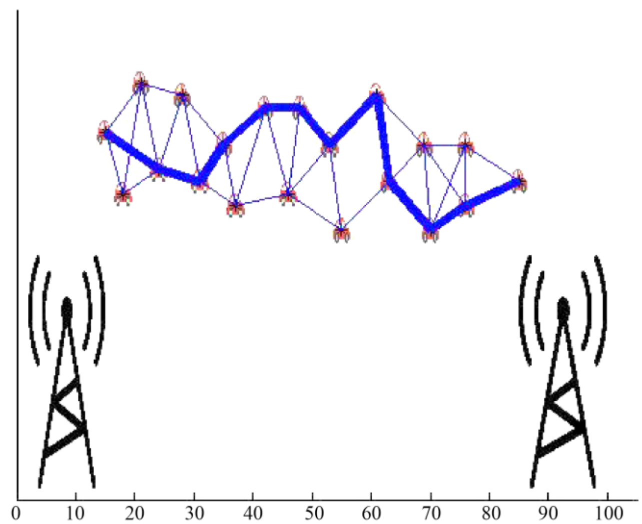

Fig. A3 Simulation results of 4th run

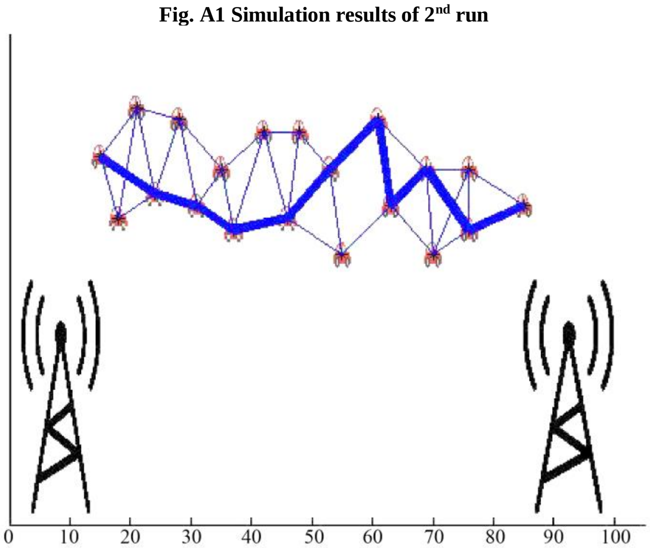

Fig. A2 Simulation results of 3rd run

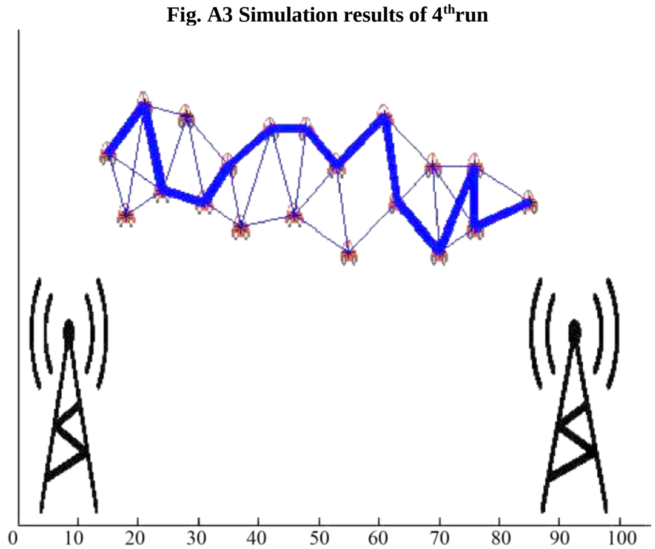

Fig. A4 Simulation results of 5th run

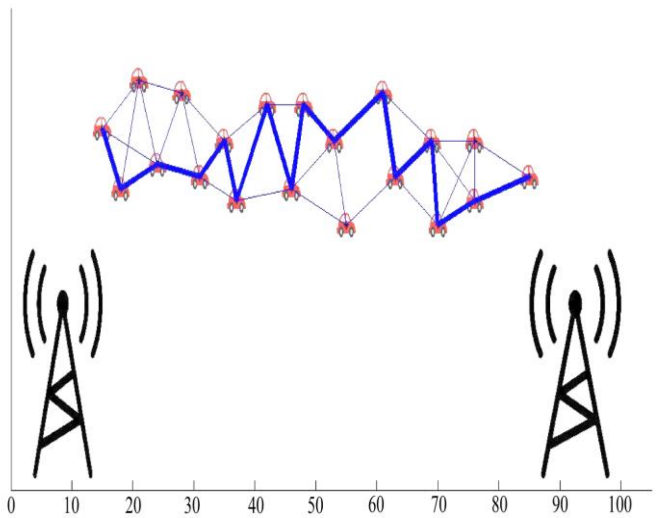

Fig. A5 Simulation results of 6thrun

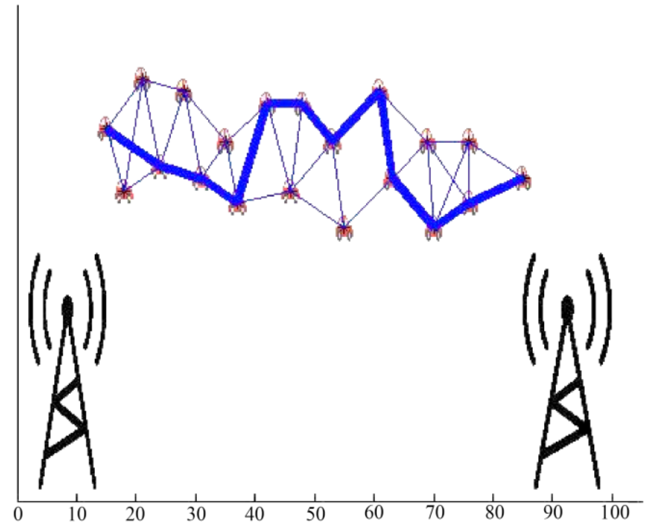

Fig. A7 Simulation results of 8thrun

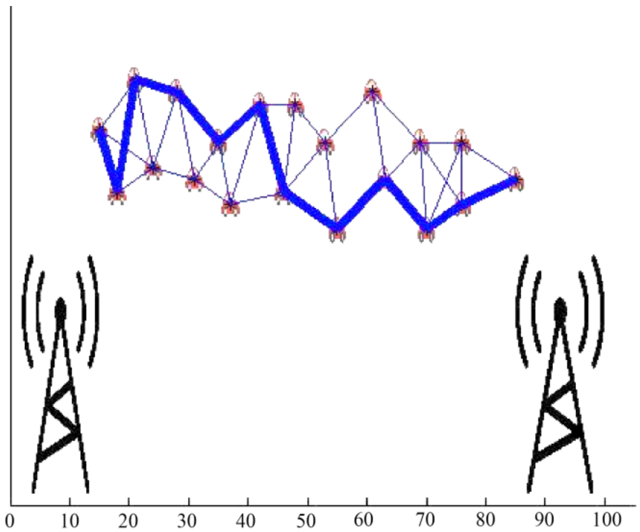

Fig. A6 Simulation results of the 7thrun

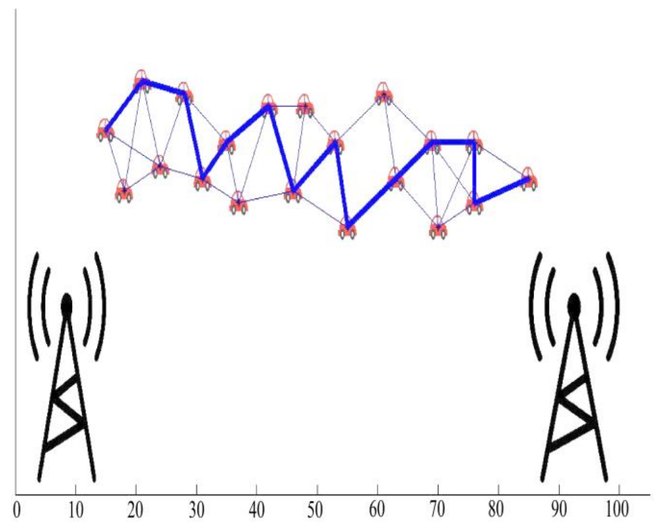

Fig. A8 Simulation results of the 9thrun

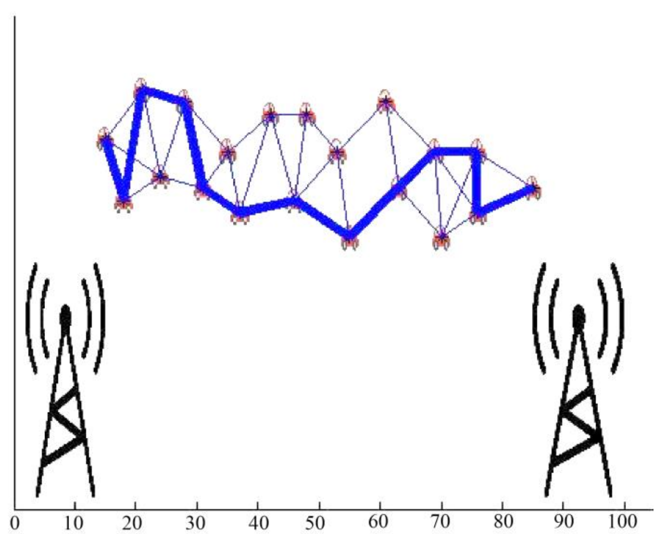

Fig. A9 Simulation results of 10thrun